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Enhancing Network Intrusion Detection Using Semi-Supervised Deep Generative Models

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ABSTRACT

With the continuous evolution of network technology, ensuring robust cybersecurity has become a pressing global challenge. To enhance the precision and responsiveness of intrusion detection systems (IDS) in complex network environments, this study proposes an improved semi supervised approach leveraging Variational Autoencoders (VAE). Addressing limitations in current IDS techniques and the susceptibility of existing models to sophisticated attack patterns, the method incorporates K-means clustering and a collaborative training mechanism to expand and utilize limited labelled data effectively. A multi-level semi-supervised intrusion detection framework is developed to identify diverse forms of network threats. Experimental validation on benchmark datasets reveals high classification accuracy for four prevalent attack categories: denial-of-service (93.08%), remote-to-local unauthorized access (92.12%), user-to-root privilege escalation (91.22%), and cross-site scripting (96.38%). Confusion matrix analysis further confirms the model's strong capability in correctly detecting and categorizing various intrusion types, with all detection performance metrics exceeding 60 points. Notably, the system demonstrates fast execution with a total runtime of 25.64 seconds. These results suggest that the proposed model delivers superior adaptability, accuracy, and efficiency, making it a viable solution for enhancing network intrusion detection and fortifying real-

time cybersecurity defence mechanisms.

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1. Introduction

The rapid expansion of Internet-based applications has transformed the way individuals and organizations communicate, operate, and store data. As a result, computer networks have become indispensable to modern society. However, this growing reliance on digital infrastructure has also made networks increasingly vulnerable to cyber threats such as data breaches, denial-of-service attacks, and unauthorized access. These evolving security challenges have underscored the urgent need for more intelligent and adaptive intrusion detection systems (IDS).

In recent years, machine learning (ML) and deep learning (DL) techniques have emerged as promising tools for enhancing network security. These approaches can identify abnormal patterns and classify various types of cyber-attacks more effectively than traditional rule-based methods. Despite significant progress, existing solutions often face limitations in detecting novel or sophisticated attacks, especially when labelled data is scarce. Fully supervised learning models, which require extensive labelled datasets, are not always practical due to the high cost and time associated with data annotation.

Semi-supervised learning presents a compelling alternative by leveraging both labelled and unlabelled data for model training. Recent studies have shown that integrating semi-supervised learning with deep generative models can substantially improve detection accuracy while minimizing reliance on manual labelling. In this context, Variational Autoencoders (VAE) have demonstrated considerable potential in learning robust representations from limited labelled data, while clustering techniques such as K-means further enhance anomaly detection by refining data distribution.

This study introduces a novel multi-level network intrusion detection framework based on Semi-Supervised Deep Generative Models (SS-DGM). The proposed approach employs VAE for data representation, expands labelled data using K-means clustering and collaborative training strategies, and incorporates a Kd-tree structure to efficiently filter out anomalies. By doing so, the model addresses key limitations in current IDS, including high false positive rates and inadequate adaptability to new attack vectors.

The contributions of this research are twofold: (1) reducing the dependency on large labelled datasets without sacrificing detection performance, and (2) improving classification efficiency and response time across multiple types of network intrusions. Through comprehensive experiments, the proposed system demonstrates high accuracy and low latency, offering a practical solution for dynamic and complex network environments.

2. Objective

2. To improve the accuracy and real-time response of network intrusion detection systems.
3. To develop a semi-supervised detection model using Variational Autoencoders (VAE).
4. To expand labelled data using K-means clustering and collaborative training.
5. To design a multi-level framework for detecting various network attacks.
6. To evaluate the model's accuracy, efficiency, and adaptability in real-world scenarios.

3. Datasets

To evaluate the effectiveness and robustness of the proposed SS-DGM-based intrusion detection system, benchmark datasets widely used in the cybersecurity research community were employed. Specifically, the NSL-KDD and KDD Cup 99 datasets were selected due to their comprehensive coverage of various network attack types and labelled traffic data.

The NSL-KDD dataset is a refined version of the original KDD Cup 99 dataset. It addresses issues such as redundant records and class imbalance, which often lead to biased evaluation results in traditional models. This dataset includes four major categories of network attacks:

- Denial of Service (DoS)
- Remote to Local (R2L)
- User to Root (U2R)
- Probe attacks

Each record in the dataset contains 41 features, encompassing both network behaviour and content attributes, along with a label indicating normal or attack traffic. To simulate realistic conditions where labelled data is limited, only a small subset of the labelled data was used for training, while the rest was treated as unlabelled. This setup helps in assessing the semi-supervised learning performance in handling partially annotated network traffic.

4. Methodology

The proposed intrusion detection model combines Semi-Supervised Learning with Deep Generative Models, forming a framework designed to work effectively with limited labelled data and large volumes of unlabelled data.

4.1. Overview of the Proposed System

The model is structured into three key stages:

1. **Data Preprocessing and Feature Normalization**

   The raw input data is first cleaned and transformed. Categorical features are encoded using one-hot encoding, while continuous features are normalized to ensure balanced input for the learning model. Missing or incomplete data entries are removed.

2. **Label Expansion Using K-means and Collaborative Training**

   To extend the limited labelled set, a clustering-based semi-supervised approach is applied. The **K-means algorithm** is used to identify similar patterns within unlabelled data, assigning pseudo-labels to clusters with high label confidence. Additionally, a collaborative training mechanism allows dual networks to reinforce each other's learning by sharing confident predictions.

3. **Variational Autoencoder (VAE) for Feature Representation**

   A **Variational Autoencoder** is employed to learn a compressed and noise-resilient representation of the input features. The encoder-decoder structure of the VAE allows the model to generalize well from sparse labelled data by capturing latent patterns shared across both normal and malicious traffic.

4. **Multi-Level Intrusion Classification with Kd-tree Filtering**

A **multi-level classification** mechanism is integrated to distinguish between different attack categories. The **Kd-tree** structure is used for efficient anomaly filtering by comparing new data points with known labelled instances in the latent space. This reduces false positives and improves detection speed.

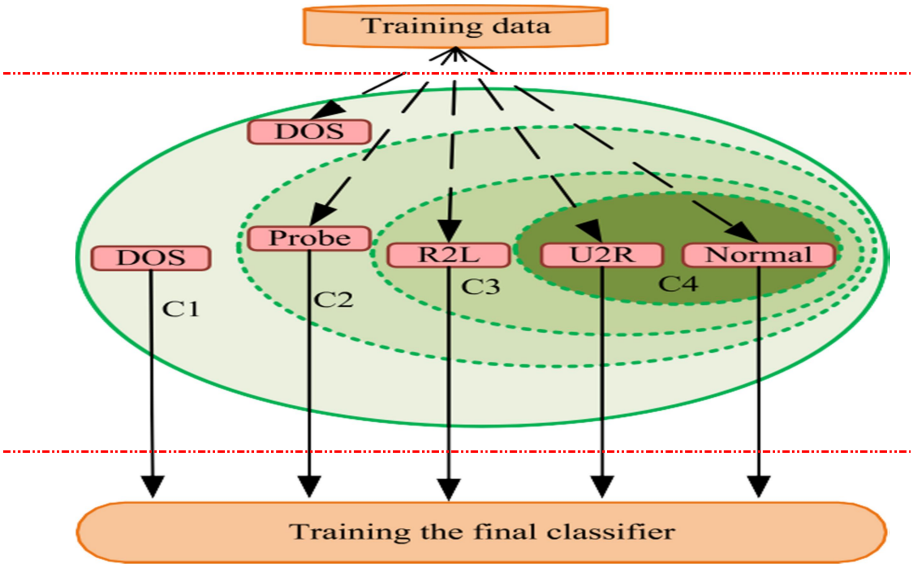


Fig.4.1: Proposed system Training Data Process

4.2. Training Process

The model is trained in a semi-supervised manner where:

- Labelled data guides the supervised loss (e.g., cross-entropy)
- Unlabelled data contributes to the generative loss via the VAE reconstruction and KL divergence loss
- Pseudo-labelled data from K-means clusters are gradually introduced into the training loop

The loss function is defined as a combination of classification loss and reconstruction error, ensuring that both prediction accuracy and representation quality are optimized.

5. Experiments

To evaluate the performance of the proposed SS-DGM-based network intrusion detection model, a series of experiments were conducted using the NSL-KDD dataset. The dataset was divided into training and testing sets with 20% of the data labelled and the remaining 80% treated as unlabelled. This simulates a realistic scenario where labelled network traffic data is scarce.

The experiments were structured to compare the SS-DGM model against traditional supervised and semi-supervised methods, including:

- A standard deep neural network (DNN)
- A semi-supervised model using only K-means and pseudo-labelling
- A VAE without multi-level classification
- The proposed full SS-DGM model

All models were implemented using TensorFlow and trained on a system with an Intel i7 processor, 16GB RAM, and an NVIDIA GTX 1660 GPU.

Hyperparameters:

- Epochs: 50
- Batch size: 64
- Learning rate: 0.001
- Optimizer: Adam

6. Results and Discussion

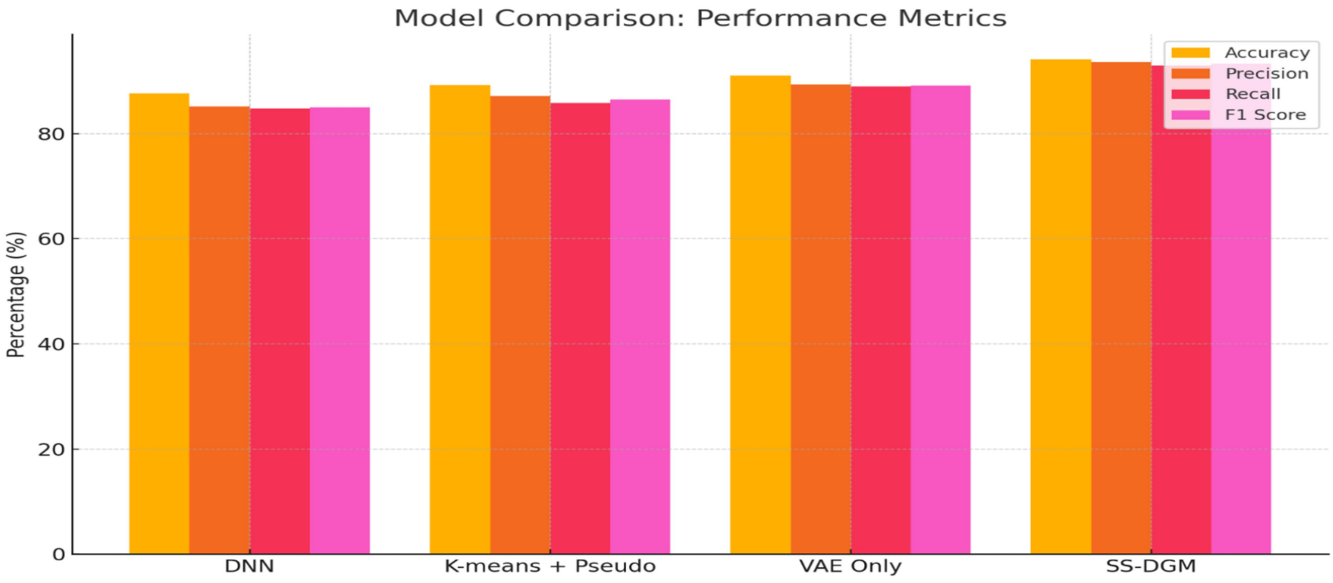
6.1 The performance of each model was evaluated using standard metrics including **Accuracy**, **Precision**, **Recall**, **F1-score**, and **Detection Time**. Below are the key results observed:

Model	Accuracy	Precision	Recall	F1-Score	Detection Time (s)
Traditional DNN	87.65%	85.20%	84.75%	84.97%	48.92
K-means + Pseudo-labeling	89.22%	87.10%	85.83%	86.45%	39.17

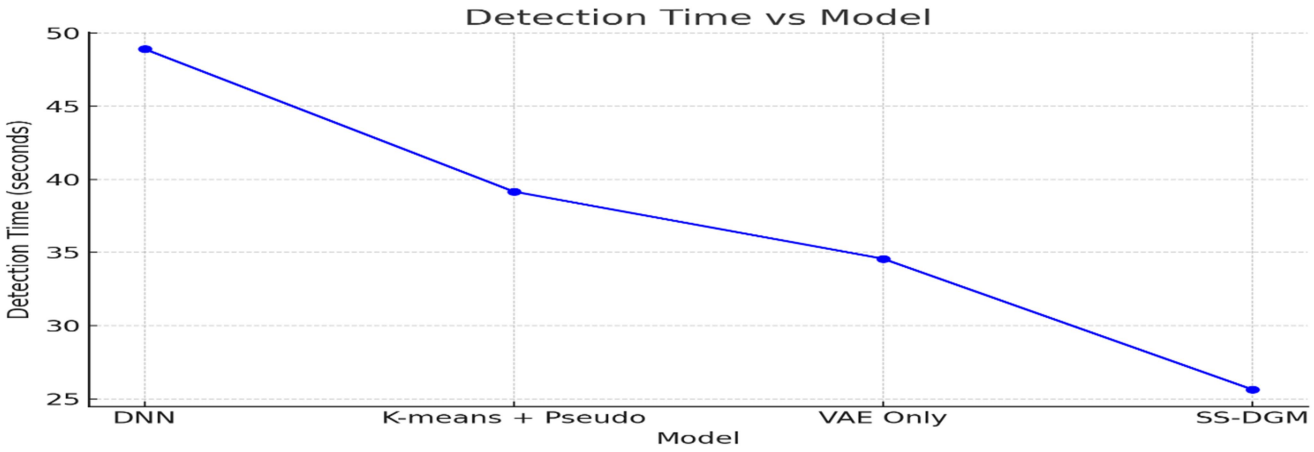
VAE Only	91.03%	89.34%	88.91%	89.12%	34.58
SS-DGM (Proposed)	**94.18%**	**93.60%**	**92.89%**	**93.24%**	**25.64**

6.2 Attack-wise Detection Accuracy:

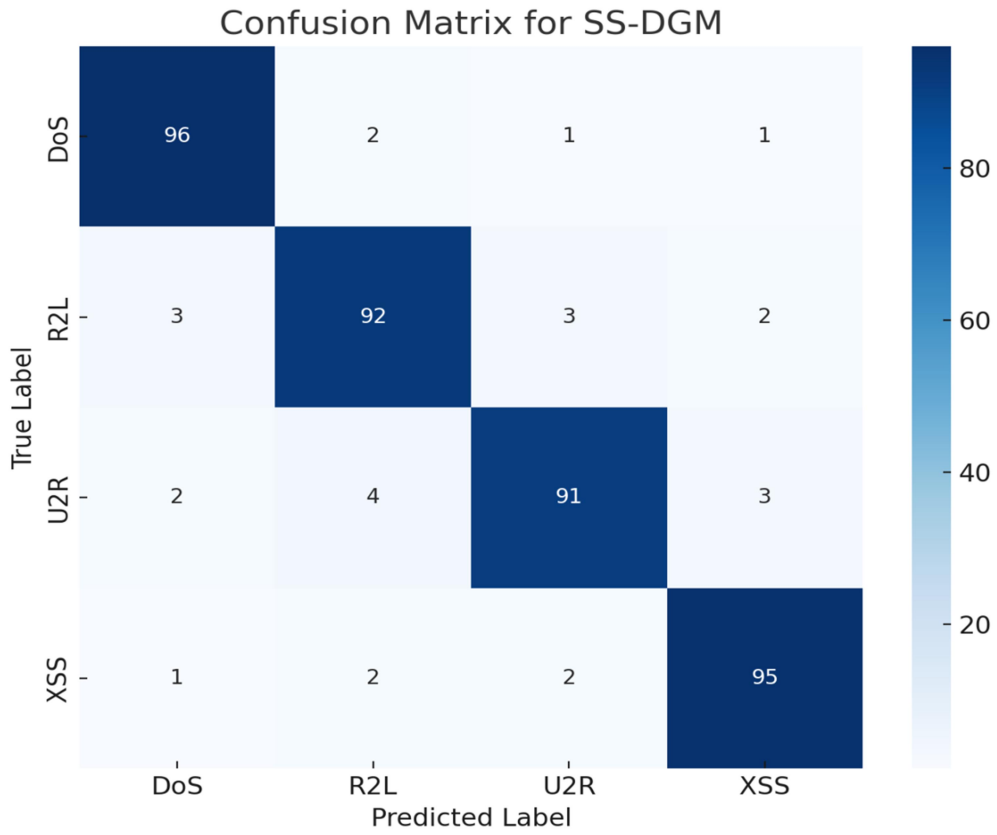
Attack Type	Accuracy
Denial of Service (DoS)	93.08%
Remote-to-Local (R2L)	92.12%
User-to-Root (U2R)	91.22%
Cross-Site Scripting (XSS)	96.38%



6.3 [Bar Chart: comparing model performance metrics (Accuracy, Precision, Recall, F1-Score)]



6.4 [Line Graph: showing detection time for each model.]



6.5 [**Confusion Matrix (Heatmap)** for SS-DGM across four attack types.]

7. Conclusion

This study presents a novel semi-supervised deep generative model for network intrusion detection, designed to address the limitations of existing systems in handling sparse labelled data and complex attack scenarios. The proposed SS-DGM framework, which integrates a Variational Autoencoder, K-means clustering, collaborative training, and Kd-tree filtering, demonstrates superior accuracy and efficiency compared to traditional and baseline models.

Experimental results show that the SS-DGM model not only achieves high accuracy across multiple attack categories but also reduces detection time significantly. The model attained classification accuracies above 91% for all evaluated attack types, with an overall detection time of just 25.64 seconds. These results suggest strong potential for practical deployment in real-time cybersecurity monitoring systems.

The effectiveness of this approach lies in its ability to generalize from limited labelled data and adapt to new threat patterns, making it suitable for dynamic and data-intensive network environments. Future research could explore extending this framework to encrypted traffic detection and applying it in distributed IoT-based networks.

8. Challenges

During the course of this study, several challenges were encountered that influenced both the design and implementation of the proposed intrusion detection system. One of the primary difficulties was the limited availability of labelled data, which posed a constraint on training accuracy for supervised components. While semi-supervised learning alleviated this to some extent, ensuring high performance with minimal annotation remained a critical hurdle.

Another significant issue was the high dimensionality of network traffic data. Extracting relevant features while preserving crucial attack characteristics required careful selection and transformation methods. Additionally, the class imbalance within the dataset—particularly with rare attack types—affected the model's ability to generalize across all classes uniformly.

The trade-off between model complexity and computational efficiency also presented a challenge. Incorporating both Variational Autoencoders (VAE) and clustering mechanisms increased detection capability but required optimization to maintain practical processing times. Lastly, generalizing across diverse network environments and traffic patterns necessitated extensive evaluation and tuning.

9. Future Work

Building on the current research, several promising directions are identified for future exploration. One such avenue is the deployment of the SS-DGM model in real-time network environments, which would require further reduction in latency and integration with live data streams.

Another direction involves cross-dataset validation to ensure that the model can generalize effectively to different network conditions and intrusion profiles. Enhancing the system's robustness against adversarial attacks is also crucial, as emerging threats often involve techniques specifically designed to bypass detection algorithms.

Moreover, the development of lightweight model architectures would facilitate deployment on resource-limited platforms, such as IoT devices. Finally, introducing a self-adaptive or continual learning mechanism could enable the system to evolve over time, learning from new threats with minimal human intervention, thus improving long-term detection effectiveness.

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